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Backtesting VaR in consideration of the higher moments of the distribution for minimum-variance hedging portfolios

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ABSTRACT

The higher moments of a distribution often lead to estimated value-at-risk (VaR) biases. This study's objective is to examine the backtesting of VaR models that consider the higher moments of the distribution for minimum-variance hedging portfolios (MVHPs) of the stock indices and futures in the Greater China Region for both short and long hedgers. The results reveal that the best backtesting VaR for the MVHP considered both the higher moments of the MVHP distribution and the asymmetry in volatility, cross-market asymmetry in volatility, and level effects in the covariance matrix of assets in the MVHP. These empirical results provide references for investors in risk management.

1. Introduction

The occurrence of numerous incidents related to inappropriate risk management, such as those involving the Orange County government and JP Morgan Chase and Co., have motivated companies to emphasize risk management and profitability. Furthermore, the implementation of the Basel II Accord by the Basel Committee on Banking Supervision at the Bank for International Settlements signifies the determination that risk management methods have become a central issue for financial institutions and companies globally.

Ensuring accuracy is the main issue in applying value-at-risk (VaR) models. In 1996, the Basel Committee on Banking Supervision amended the Basel Accord to require that banks approximate suitable capital adequacy using an internal VaR model and conduct backtests to assess the model's reliability. When asset returns display heavy tails or skewness, t distribution outperforms normal distribution for estimating VaR. Chong (2004) and So and Yu (2006) discovered that t distributions can better capture heavy tails in asset returns. However, t distributions underperform asset returns in identifying skewness. Thus, Favre and Galeano (2002) proposed a mean-modified VaR optimization model that utilizes the higher moments of the distribution to capture both heavy tails and skewness. Favre and Galeano (2002) also found that a mean-modified VaR optimization model is necessary for VaR estimation.

The volatility clustering that is common in financial data can be identified using a univariate generalized autoregressive conditional heteroskedasticity (GARCH) model (Baillie and Myers, 1991; Bollerslev, 1986; Engle, 1982). However, the inability of the GARCH model to capture asymmetry in volatility led Glosten et al. (1993) to develop the univariate Glosten, Jagannathan and Runkle (GJR) model. Pochon and Teiletche (2007) and Mokni et al. (2009) have reported that, in addition to the better capturing asymmetry in volatility, the VaR performance of the GJR model was superior to that of the GARCH model. However, interactions between asymmetry in volatility have commonly occurred in the asset returns of hedging portfolios; therefore, researchers proposed the bivariate asymmetric diagonal VECH (ADVECH) model to capture the asymmetry in and cross-market asymmetry in volatility in the covariance matrix of assets in the portfolio (Cotter and Hanly, 2012; De Goeij and Marquering, 2004). In addition, the vector error correction (VEC) model can solve the problem of long-term information loss when taking the difference of time series. Thus, Chuang et al. (2012) proposed the multivariate VEC-ADVECH model that can simultaneously reveal long-term deviations among variables in mean equations and the asymmetry in volatility, the cross-market asymmetry in volatility in the covariance matrix of assets in the hedging portfolio.

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The level effect refers to the influence of asset returns on volatility, and the predictive ability of models that consider that the level effect is superior to those of models that fail to consider it. De Goeij and Marquering (2009) extended the multivariate ADVECH model of De Goeij and Marquering (2004) into the multivariate level ADVECH (ADVECH-L) model, which can simultaneously identify level effects, asymmetry in volatility, and cross-market asymmetry in volatility in the covariance matrix of assets. However, few studies have considered the use of the multivariate VEC-ADVECH-L model to investigate the VaR performance of minimum-variance hedging portfolios (MVHPs).

In situations with heavy tails or skewness in returns on assets, using higher moments of the distribution to estimate the VaR can improve the VaR performance. This study refers to Johnson's hypotheses (1960) to establish the MVHP of the multivariate time-variant volatility model for stock indices and derived futures in the Greater China Region (i.e., the Hang Seng, Taiwan, and Shanghai A-share stock indices and futures) for short and long hedgers. Additionally, this study compares backtesting VaR performance for the MVHP both considering and without considering the higher moments of the MVHP distribution on the likelihood ratio test of Kupiec (1995) and the conditional coverage test of Christoffersen (1998).

The main contribution of the study shows, for short and long hedgers, that the backtesting for VaR performances that considers the higher moments of the distribution for the MVHP were consistently superior to performances of the model that does not consider the higher moments of the distribution for the MVHP. Additionally, the backtesting showed that the best VaR performance for the MVHP was from the model that considered the higher moments of the MVHP distribution and the asymmetry in volatility, cross-market asymmetry in volatility, and the level effects in the covariance matrix of assets in the MVHP, whereas the backtesting also showed that the worst VaR performance for the MVHP was from a model that does not consider any of the foregoing. The study results might provide a comprehensive account of portfolio theory.

The remainder of this study is organized as follows. Section 2 describes the data and model. Section 3 summarizes the empirical results. And, section 4 presents conclusions and suggestions.

2. Data and model

2.1. Data selection and sources

In 1993, the World Bank and the International Monetary Fund officially listed Taiwan, Hong Kong, and Mainland China as an economic unit. This study thus focuses on the stock indices and derived futures in the Greater China Region (i.e., the Hang Seng, Taiwan, and Shanghai A-share stock indices and futures). The data closing of stock indices and futures cover from May 14, 2010 to December 30, 2011, and the research sample is 402 observations. The data is from the Datastream database. Returns were calculated as the first difference in the natural logarithm of daily closing prices and multiplied by 100.

A rolling-window framework is used to calculate the hedge ratios of the MVHP. Observed values from date 1 to date n were first used to estimate the parameters of the variant multivariate time-variant volatility models and then to calculate the hedge ratio of the MVHP at date n + 1. Subsequently, the observed values from date 2 to date n + 1 were used to estimate the parameters of the variant multivariate time-variant volatility models and then to calculate the hedge ratio of the MVHP at date n + 2. This approach was continued until the hedge ratio of the MVHP at the last date was calculated.

2.2. Multivariate VEC-ADVECH-L model

In the multivariate VEC-ADVECH model established by Chuang et al. (2012), VEC is a vector error correction, which links the long-term equilibrium relationship that is implied by cointegration with the short-term dynamic adjustment mechanism that describes how variables react when they move out from the long-term equilibrium. In addition to sharing the characteristics of the GJR model, the ADVECH model can identify cross-market asymmetry in volatility. Embedding the level effect, the multivariate VEC-ADVECH model (simply referred to as the VEC-ADVECH-L model hereafter) yields the following:

$$r_{i,t} = a_i + b_i r_{i,t-1} + c_i\left(\ln P_{1,t-1} - \kappa - \delta \ln P_{2,t-1}\right) + d_j r_{j,t-1} + \varepsilon_{i,t}, \quad i,j = 1,2 \;,\; i \neq j \tag{1}$$

$$\begin{aligned}\sigma_{ij,t} = \left|r_{i,t-1} r_{j,t-1}\right|^{\gamma_{ij}} \times \Big(&\tau_{ij} + \alpha_{1ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \alpha_{2ij} I_{\varepsilon_{i,t-1}} \quad \varepsilon_{i,t-1} I_{\varepsilon_{j,t-1}} \varepsilon_{j,t-1} \\ &+ \alpha_{3ij}\left(1 - I_{\varepsilon_{i,t-1}}\right)\varepsilon_{i,t-1} I_{\varepsilon_{j,t-1}} \varepsilon_{j,t-1} \quad + \alpha_{4ij} I_{\varepsilon_{i,t-1}} \varepsilon_{i,t-1}\left(1 - I_{\varepsilon_{j,t-1}}\right)\varepsilon_{j,t-1} \\ &+ \beta_{ij}\sigma_{ij,t-1}\Big), \qquad i,j = 1,2\end{aligned} \tag{2}$$

$$\rho_{ij,t} = \frac{exp\left(q_{ij,t}\right)}{1 + exp(q_{ij,t})}, \quad i,j = 1,2 \;,\; i \neq j \tag{3}$$

$$q_{ij,t} = \varpi_0 + \varpi_1 \rho_{ij,t-1} + \varpi_2 \frac{\varepsilon_{i,t-1}\varepsilon_{j,t-1}}{\sqrt{\sigma^2_{ii,t-1}\sigma^2_{jj,t-1}}}, \qquad i,j = 1,2 \;,\; i \neq j \tag{4}$$

where Eq. (1) represents the mean equation for returns on asset i and $r_{i,t}$ represents the returns on asset i at time t. The speed of adjustment toward equilibrium is determined by the magnitude of c_i. Moreover, Eq. (2) is the conditional covariance of the returns on assets i and j at time t. Moreover, α_{1ij} captures the interaction effect of shocks between returns on assets i and j at time t-1. Thus, α_{2ij} captures the asymmetric interaction effect of return shocks between assets i and j at time t-1. If $\varepsilon_{k,t-1} < 0$, $I_{\varepsilon_{k,t-1}}$ is defined as 1; otherwise, it is 0. Additionally, β_{ij} denotes the effects of the conditional covariance of returns on assets i and j at time t-1. In addition, α_{3ij} and α_{4ij} represent the effects of cross-market asymmetry in volatility. Moreover, γ_{ij} is used to capture the impact of level effects. Consequently, if γ_{ij} is not 0, the conditional covariance is determined by the product of returns on assets i and j as well as and information shocks. The larger γ_{ij} is, the more level effects are. If γ_{ij} is 0, the conditional covariance is only determined by information shocks i.e., it is the VEC-ADVECH model. Eqs. (3) and (4) are based on the dynamic conditional correlation proposed by Tsay (2009), where $\rho_{ij,t}$ represents the dynamic conditional correlation coefficient of returns on assets i and j at time t. Additionally, $q_{ij,t}$ denotes the covariance between returns on assets i and j at time t, whereas ϖ_1 represents the intertemporal persistence of the dynamic conditional correlation coefficient of returns on assets i and j. Furthermore, ϖ_2 denotes the dynamic conditional correlation coefficient between returns on assets i and j that is influenced by normalization shocks at time t-1. Finally, Table 1 compares the specifications of the models and the parameter-related restrictions.

Table 1
Comparison of model specifications and parameter restrictions.

Model	γ	α_2	α_3	α_4
VEC-DVECH	0	0	0	0
VEC-ADVECH	0	Unrestricted	Unrestricted	Unrestricted
VEC-DVECH-L	Unrestricted	0	0	0
VEC-ADVECH-L	Unrestricted	Unrestricted	Unrestricted	Unrestricted

Note: VEC-DVECH denotes a multivariate DVECH model with a vector error correction term. VEC-ADVECH represents a multivariate ADVECH model with a vector error correction term. VEC-DVECH-L is a multivariate DVECH-L model with a vector error correction term. VEC-ADVECH-L denotes a multivariate ADVECH-L model with a vector error correction term.

Because the log likelihood function is a nonlinear function of the parameters in the empirical model, this study used the BHHH algorithm that was proposed by Berndt et al. (1974) to obtain the maximum likelihood estimates of the parameters.

2.3. VaR model for MVHP of short and long hedgers

Let β_t be the hedge ratio of MVHP and let $r_{i,t}$ be the returns on asset i at time t, then the returns of the MVHP at time t are $r_{p,t} = r_{i,t} - \beta_t r_{j,t}$ for short hedgers and $r_{p,t} = -r_{i,t} + \beta_t r_{j,t}$ for long hedger. At a confidence level of $1 - \alpha$, the VaR model for the MVHP of short hedgers is

$$VaR_{p,t}^{short} = \mu_{p,t} + \delta_{1-\alpha}\sigma_{p,t} \tag{5}$$

and the VaR model for the MVHP of long hedgers is

$$VaR_{p,t}^{long} = \mu_{p,t} + \delta_{\alpha}\sigma_{p,t} \tag{6}$$

where $VaR_{p,t}^{short}(VaR_{p,t}^{long})$ represents the VaR of the MVHP returns at time t for short (long) hedgers, $\sigma_{p,t} = \sqrt{\boldsymbol{w}' \sum \boldsymbol{w}}$ is the standard deviation of the MVHP returns at time t, and $\boldsymbol{w}$ and $\sum$ represent the weight vector and covariance matrix of the various asset returns in the MVHP, respectively. When the higher moments of the MVHP distribution are ignored, δ_α is set as the αth percentile of the standard normal distribution. This study sets α as 1% and 5%. When the higher moments of the MVHP distribution are considered, we follow the approach of the mean-modified VaR optimization model proposed by Favre and Galeano (2002) (simply labeled the FG model hereafter), setting δ_α as

$$\delta_\alpha = z_\alpha + (1/6)\left(z_\alpha^2 - 1\right)S_p + (1/24)\left(z_\alpha^3 - 3z_\alpha\right)K_p - (1/36) \times \left(2z_\alpha^3 - 5z_\alpha\right)S_p^2, \tag{7}$$

where z_α represents the αth percentile of the standard normal distribution, and S_p and K_p represent the skewness and kurtosis of the MVHP returns, respectively. Pochon and Teiletche (2007) list the δ_α values under different levels of significance.

The likelihood ratio test of Kupiec (1995) is used to compare the backtesting of the VaR performance for the MVHP from variant multivariate time-variant volatility models in this study. However, the numbers failure series may be clustered, and the conditional coverage test of Christoffersen (1998), which is a joint test of unconditional coverage and serial independence, is also used to compare the VaR performance for the MVHP from the variant multivariate time-variant volatility models in this study.

Table 3
Average hedge ratios of the MVHP.

Model	Hang Seng	Taiwan	Shanghai A
Panel A: without considering the higher moments of the MVHP distribution.			
VEC-DVECH	0.9529	0.8984	0.9117
VEC-ADVECH	0.9102	0.8114	0.8114
VEC-DVECH-L	0.9106	0.8427	0.8427
VEC-ADVECH-L	0.9107	0.7916	0.7029
Panel B: considering the higher moments of the MVHP distribution.			
VEC-DVECH	0.9414	0.8903	0.8903
VEC-ADVECH	0.9217	0.6962	0.6969
VEC-DVECH-L	0.9234	0.7812	0.7585
VEC-ADVECH-L	0.8988	0.7055	0.7608

Note: VEC-DVECH is a multivariate DVECH model with a vector error correction term. VEC-ADVECH denotes a multivariate ADVECH model with a vector error correction term. VEC-DVECH-L represents a multivariate DVECH-L model with a vector error correction term. VEC-ADVECH-L denotes a multivariate ADVECH-L model with a vector error correction term.

3. Empirical results

Table 2 lists the summary of statistics. At a significance level of 5%, the Jarque–Bera test statistics of the stock indices and futures in the Greater China Region did not support that any one follows normal distribution. Table 3 lists the hedge ratios of the MVHP for stock indices and futures in the Greater China Region. Ignoring the higher moments of the MVHP distribution, the hedge ratios of the MVHP ranged between 0.7029 and 0.9529. When the higher moments of the MVHP distribution were considered, the hedge ratios ranged between 0.6962 and 0.9414. Regardless of whether the higher moments of the MVHP distribution were considered, the hedge ratios of the MVHP were all below 1 and above 0, which indicates the applicability of futures for hedging in the Greater China Region.

After calculating the VaR values of the MVHP from variant multivariate time-variant volatility models, this study employed the likelihood ratio test from Kupiec (1995) and the conditional coverage test of

Table 2
Summary of statistics.

Statistics	Hang Seng		Taiwan		Shanghai A	
	Stock index	Futures	Stock index	Futures	Stock index	Futures
Mean	−0.0426	−0.0396	−0.0342	−0.0341	−0.0882	−0.0941
Standard deviation	1.4139	1.4390	1.2524	1.3474	1.3534	1.5438
Skewness	−0.3213	−0.1923	−0.3744	−0.3265	−0.5017	−0.3311
Excess kurtosis	4.8402	3.9239	1.8755	2.0549	1.5865	2.8027
Jarque–Bera	63.4804[b]	16.7347[b]	68.1398[b]	77.6775[b]	58.8795[b]	138.5696[b]
LB Q (12)	16.4090[a]	17.0850[b]	31.9780	21.6390	15.8200	18.1770
LB Q^2(12)	57.5640[b]	54.1410[b]	66.1260[b]	54.0330[b]	10.3970	11.6410
SBT	0.9905	3.78160[a]	9.6633[b]	3.7519	2.0548	0.5474
	(1.9476)	(1.6942)	(1.9565)	(1.9943)	(1.8798)	(2.1774)
NSBT	2.0041	0.3701	27.4099[b]	13.5797[b]	1.6253	0.0297
	(1.9466)	(1.7031)	(1.8783)	(1.9862)	(1.7906)	(1.9693)
PSBT	0.8075	1.0750	3.4939	2.3483	0.0050	0.0021
	(1.9496)	(1.7016)	(1.9335)	(1.9862)	(1.7906)	(1.9693)
JT	84.6751[a]	105.7350[a]	103.0610[a]	90.2348[a]	92.2939[a]	75.9020[a]

2. LB Q (12) represents Ljung-Box Q test statistics of lag 12; the critical value is 26.217 (21.0261) at the 1% (5%) significant level.
3. LB Q^2 (12) refers to Ljung-Box Q test statistics of lag 12 for squared series; the critical value is 26.217 (21.0261) at the 1% (5%) significant level.
4. SBT, NSBT, PSBT, and JT refer to the sign bias test (SBT), negative size bias test (NSBT), positive size bias test (PSBT), and joint test (JT) proposed by Engle and Ng (1993). JT is a chi-square distribution with 3° of freedom. The critical value is 7.82 at the 5% significant level.
5. The figures in brackets denote standard errors.
[a] Statistical significance at the 5% significant level.
[b] Statistical significance at the 1% significant level.

Table 4
Backtesting VaR for the MVHP of short hedgers.

Model	Hedging portfolio	Number of failures		LR_{uc}		LR_{cc}	
		1%	5%	1%	5%	1%	5%
Panel A: without considering the higher moments of the MVHP distribution.							
VEC-DVECH	HS	5	12	**4.2930**	**1.3968**	**6.2905**	**3.0791**
	TW	8	13	12.4964	**2.2305**	13.6960	**3.8340**
	SA	9	16	15.8091	5.6903	17.7114	7.4157
VEC-ADVECH	HS	3	9	**0.8336**	**0.0369**	**2.8314**	**1.5585**
	TW	6	10	6.6964	**0.2834**	**8.4846**	**1.8049**
	SA	7	14	9.4469	**3.2311**	11.2128	**4.9682**
VEC-DVECH-L	HS	4	7	**2.3046**	**0.2775**	**3.7811**	**1.7744**
	TW	5	9	**4.2930**	**0.0369**	**5.9835**	**1.7039**
	SA	6	12	6.6964	**1.3968**	**8.4303**	**3.3462**
VEC-ADVECH-L	HS	2	5	**0.0542**	**1.7263**	**2.0523**	**2.9059**
	TW	3	6	**0.8336**	**0.8283**	**2.2148**	**2.5664**
	SA	4	10	**2.3046**	**0.2834**	**4.2987**	**2.1958**
Panel B: considering the higher moments of the MVHP distribution.							
VEC-DVECH	HS	4	11	**2.3046**	**0.7428**	**3.9272**	**2.2314**
	TW	6	10	6.6964	**0.2834**	**7.6962**	**2.2721**
	SA	8	14	12.4964	**3.2311**	14.1632	**4.8836**
VEC-ADVECH	HS	2	7	**0.0542**	**0.2775**	**2.0523**	**1.6080**
	TW	5	9	**4.2930**	**0.0369**	**5.9712**	**1.9286**
	SA	6	11	6.6964	**0.7428**	**8.6937**	**2.5130**
VEC-DVECH-L	HS	3	6	**0.8336**	**0.8283**	**2.8336**	**1.8282**
	TW	4	7	**2.3046**	**0.2775**	**4.3046**	**1.7744**
	SA	5	9	**4.2930**	**0.0369**	**6.2864**	**1.7039**
VEC-ADVECH-L	HS	1	4	**0.3334**	**3.0392**	**0.3334**	**4.6618**
	TW	2	4	**0.0542**	**3.0392**	**1.1813**	**5.0348**
	SA	3	7	**0.8336**	**0.2775**	**2.8314**	**1.7744**

Note: 1. VEC-DVECH is a multivariate DVECH model with a vector error correction term. VEC-ADVECH denotes a multivariate ADVECH model with a vector error correction term. VEC-DVECH-L represents a multivariate DVECH-L model with a vector error correction term. VEC-ADVECH-L denotes a multivariate ADVECH-L model with a vector error correction term.
2. HS, TW, and SA denote the Hang Seng, Taiwan, and Shanghai A stock indices and futures portfolios, respectively.
3. The boldface numerics in the table indicate no significance at their corresponding levels determined through backtesting.
4. LR_{uc} denotes the likelihood ratio test, which is a chi-square distribution with 1° of freedom. The critical value is 6.6349 (3.8415) at the 1% (5%) significant level.
5. LR_{cc} denotes the conditional coverage test, which is a chi-square distribution with 2° of freedom under null hypothesis. The critical value is 9.210 (5.992) at the 1% (5%) significant level.

Christoffersen (1998) to perform backtesting for VaR performance. Tables 4 and 5 list the backtesting VaR performances for the MVHP of short and long hedgers, respectively. For both types of hedgers, consistently fewer failures are generated when the higher moments of the MVHP distribution are considered than when they are not considered, which demonstrates that the VaR of the MVHP should consider the higher moments of the MVHP distribution, and supports the conclusions of Favre and Galeano (2002). Regardless of whether we consider the higher moments of the MVHP distribution, the VEC-ADVECH model passed the backtests. The ranking of backtesting VaR performance among researched models is VEC-ADVECH-L, VEC-DVECH-L, VEC-ADVECH, and the VEC-DVECH model in descending order on the likelihood ratio test of Kupiec (1995) by means of pairwise comparisons. These results demonstrate the ability of the VEC-ADVECH model to improve VaR performance and to capture asymmetry and cross-market asymmetry in the volatility of the covariance matrix of assets in the MVHP. These findings support the findings of Chuang et al. (2012). Furthermore, models incorporating the level effect produced fewer numbers of failures than those without level effect for both short and long hedgers. This phenomenon demonstrates that backtesting VaR performances for the MVHP should embed the level effect in the covariance matrix of assets in the MVHP.

Based on the conditional coverage test, the backtesting VaR that does not consider the higher moments of the distribution for the MVHP from the VEC-DVECH model is significant for short hedgers on the Shanghai A-share stock index and futures at the 5% significant level. By contrast, the backtesting VaR that considers higher moments of the distribution for the MVHP from the VEC-DVECH model is not significant for short hedgers. This indicates that the failure numbers of the backtesting VaR that considers the higher moments of the distribution for the MVHP from the VEC-DVECH model were serially independent and not clustered.

Generally, the conclusions are identical for short and long hedgers in the backtesting VaR performances for the MVHP for the Hang Seng, Taiwan and Shanghai A-share stock indices and futures. The backtesting VaR performance that considers the higher moments of the distribution for the MVHP were better than those of the MVHP that do not consider the higher moments of the distribution. Furthermore, the backtesting of the VaR performances of the MVHP in the variant multivariate time-variant volatility models that considered asymmetry in volatility in the covariance matrix of assets in the MVHP were superior to those that have no asymmetry in volatility. Additionally, the backtesting of the VaR performance for the MVHP in the variant multivariate time-variant volatility models with level effects in the covariance matrix of assets in the MVHP were better than those of the MVHP that have no level effect in covariance matrix of assets in the MVHP. Among the models discussed in this study, backtesting of the VaR performance that considered the higher moments of distribution for the MVHP from the VEC-ADVECH-L model is the best one for the MVHP. Moreover, the model that does not consider the higher moments of distribution for the MVHP from the VEC-DVECH model performed the worst one for the MVHP in backtesting.

4. Conclusions and suggestions

This study was in backtesting VaR that considers the higher moments of the distribution for the MVHP of the daily stock index and futures in the Greater China Region. This study constructed the MVHP from the variant multivariate time-variant volatility models for stock indices and derived futures. Furthermore, we performed the likelihood ratio of Kupiec (1995) and conditional coverage tests of Christoffersen (1998) to backtest the VaR that considered the higher moments of the MVHP from the variant multivariate time-variant volatility models for short and long hedgers.

Table 5
Backtesting VaR for the MVHP of long hedgers.

Model	Hedging portfolio	Number of failures		LR_{uc}		LR_{cc}	
		1%	5%	1%	5%	1%	5%
Panel A: without considering the higher moments of the MVHP distribution.							
VEC-DVECH	HS	8	16	12.4964	5.6903	14.3434	7.5749
	TW	8	17	12.4964	7.1312	13.4224	8.7771
	SA	10	19	19.3569	10.3993	21.2642	12.1116
VEC-ADVECH	HS	5	10	**4.2930**	**0.2834**	**6.2864**	**1.8816**
	TW	6	8	6.6964	**0.0257**	**7.6962**	**1.4724**
	SA	8	10	12.4964	**0.2834**	14.3434	**1.9815**
VEC-DVECH-L	HS	4	8	**2.3046**	**0.0257**	**4.3002**	**2.0136**
	TW	5	7	**4.2930**	**0.2775**	**5.4711**	**1.8795**
	SA	7	9	9.4469	**0.0369**	10.7774	**1.8031**
VEC-ADVECH-L	HS	3	7	**0.8336**	**0.2775**	**2.2148**	**1.3039**
	TW	2	5	**0.0542**	**1.7263**	**0.5068**	**2.3473**
	SA	4	8	**2.3046**	**0.0257**	**3.9272**	**1.6966**
Panel B: considering the higher moments of the MVHP distribution.							
VEC-DVECH	HS	6	14	6.6964	**3.2311**	**7.9523**	**5.2133**
	TW	6	14	6.6964	**3.2311**	**7.8561**	**5.1157**
	SA	8	17	12.4964	7.1312	13.9116	8.6291
VEC-ADVECH	HS	4	9	**2.3046**	**0.0369**	**3.9272**	**1.7475**
	TW	4	7	**2.3046**	**0.2775**	**3.9272**	**1.6080**
	SA	6	9	6.6964	**0.0369**	**7.8561**	**1.5585**
VEC-DVECH-L	HS	3	7	**0.8336**	**0.2775**	**1.6453**	**0.9120**
	TW	3	6	**0.8336**	**0.8283**	**2.8314**	**1.8282**
	SA	5	7	**4.2930**	**0.2775**	**5.9835**	**1.8548**
VEC-ADVECH-L	HS	2	5	**0.0542**	**1.7263**	**2.0542**	**3.4612**
	TW	1	4	**0.3334**	**3.0392**	**2.3334**	**4.6618**
	SA	3	6	**0.8336**	**0.8283**	**2.8297**	**2.6274**

Note: 1. VEC-DVECH is a multivariate DVECH model with a vector error correction term. VEC-ADVECH denotes a multivariate ADVECH model with a vector error correction term. VEC-DVECH-L represents a multivariate DVECH-L model with a vector error correction term. VEC-ADVECH-L denotes a multivariate ADVECH-L model with a vector error correction term.
2. HS, TW, and SA denote the Hang Seng, Taiwan, and Shanghai A stock indeces and futures portfolios, respectively.
3. The boldface numerics in the table indicate no significance at their corresponding levels determined through backtesting.
4. LR_{uc} denotes the likelihood ratio test, which is a chi-square distribution with 1° of freedom. The critical value is 6.6349 (3.8415) at the 1% (5%) significant level.
5. LR_{cc} denotes the conditional coverage test, which is a chi-square distribution with 2° of freedom under null hypothesis. The critical value is 9.210 (5.992) at the 1% (5%) significant level.

The backtesting VaR performance of the models that considered the higher moments of the MVHP distribution were consistently superior to that of models that do not consider such higher moments of the MVHP distribution for short and long hedgers. Additionally, the best backtesting VaR performance for the MVHP was from the model that considered the higher moments of the MVHP distribution and the asymmetry in volatility, cross-market asymmetry in volatility, and level effects in the covariance matrix of assets in the MVHP, and the worst backtesting VaR was from a model that does not consider any of the foregoing. When investors construct the MVHP for hedging, they should consider the influences of asymmetry in volatility and cross-market asymmetry in volatility, level effects in the covariance matrix of assets in the MVHP. Moreover, to consider the higher moments is an indispensable part of VaR estimation for the accuracy of risk management.

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